COMPOSITE WEIGHTS FOR THE CURRENT POPULATION SURVEY

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1. Introduction. Each month, the Bureau of Labor Statistics (BLS) publishes labor force estimates for the U.S. resident population and a variety of its demographic subgroups, e.g., teenagers, Hispanics. Published figures include estimated numbers of persons employed, unemployed, and not in the labor force, as well as relevant rates such as unemployment rates. These statistics are computed using data from the Current Population Survey (CPS), a monthly household survey the Census Bureau conducts for the BLS.

The CPS sample is a two-stage probability sample of housing units, covering the entire U.S. Each new sample unit remains in the sample for four months, leaves the sample for eight months, and then re-enters for another four months. One quarter of the sample is new (or re-entering) each month, while half of each month's sample comes from the sample for the same calendar month one year earlier. This "four-eight-four" sample rotation scheme results in positive correlation between CPS estimates from different months, improving measures of change over time. The positive correlation is further increased by composite estimation.

Composite estimation is the last in a series of estimation steps performed on CPS data, prior to seasonal adjustment. Unlike weighting techniques, composite estimation does not affect CPS micro data; composite estimates are computed using estimated totals from the various *rotation groups*—groups of respondents who enter the sample together. Since the composite estimates incorporate information from several months' data, users cannot compute composite estimates from only one month's micro data.

In this paper, we present a method of computing *composite weights* for the CPS—micro data weights that incorporate the effect of composite estimation. Data users would compute composite estimates by simply adding these weights, using only one month's CPS data. This method, suggested by Fuller (1990), also allows us to tailor the composite estimator—by varying coefficients—to the correlation structures of major labor force categories, thus improving reliability. Section 2 provides a brief overview of current CPS estimation procedures, including composite estimation. In Section 3, we describe the process of selecting compositing coefficients for different labor force categories. Section 4 contains results of an empirical study of two variants of Fuller's composite weighting method, as applied to CPS data.

2. Current CPS Estimation Procedures. For each person in the monthly CPS sample, the Census Bureau calculates a weight—a rough estimate of the number of actual persons the sample person represents. Computing the weights involves several steps: initial weights reflect probabilities of selection for the sample; these "base weights" are then adjusted upward to account for the occupied sample households not interviewed. Two types of ratio adjustments are then applied. The final ratio adjustment, a raking process, ensures that the sample weights for important population subgroups sum to population estimates that nearly equal independently derived population estimates for those groups. Our methods of computing composite weights, which we discuss in Section 4, closely resemble the current CPS raking ratio adjustment.

2.1. The CPS Raking Ratio Adjustment. Because demographic characteristics, such as age, race, and area of residence, are correlated with labor force status, CPS estimates should reflect the distributions of these traits in the population. Accordingly, the Census Bureau adjusts weights for CPS sample persons aged 16 or over to agree with three sets of population estimates: population by state, by age/sex/ethnicity group, and by age/sex/race group. (Only two ethnicities, Hispanic and non-Hispanic, are considered in the adjustment.) These population estimates, often called raking "controls," are based on the most recent decennial census, corrected to account for changes since the census time. Because the composite estimation step follows ratio adjustment and reweights the data according to sample rotation group, the raking is performed separately within each of these groups. For a description of the actual raking process, see *Current Population Survey: Design and Methodology*, p. 59 (Technical Paper 40, U.S. Bureau of the Census, 1977).

2.2. The CPS Composite Estimator. Each monthly CPS sample comprises eight rotation groups, which are distinguished by the number of monthly interviews they have completed. A separate set of labor force estimates may be computed from each rotation group's data. We use the notation of Cantwell and Ernst (1993): for $i = 1,...,8$, let $x_{h,i}$ be a labor force estimator of total (e.g., total unemployed) for month h, computed using data from the *i*th rotation group. That is, $x_{h,i}$ is eight times the sum of the sample weights, after raking, of respondents in the specified labor force category who completed their *i*th interview in month *h*. Then $Y_h = \frac{1}{8}\sum_{i=1}^{8} x_{h,i}$ is the CPS ratio estimator for the labor force category.

The CPS composite estimate for a given labor force characteristic is based on a weighted average of two estimates for the same characteristic: (1) the CPS ratio estimate and (2) the previous month's composite estimate *plus* an estimate of change since the previous month. Because of the "four-eight-four" sample rotation pattern, six of the eight rotation groups in the sample for month *h*-1 remain in sample for month *h*. Thus for $i \in S$, where $S = \{2,3,4,6,7,8\}$, positive correlation between $x_{h,i}$ and $x_{h-1,i-1}$ serves to reduce the variance of estimates of change computed from these figures. So the change in the labor force characteristic since the previous month is estimated here by

$$\Delta_h = \frac{1}{6}\sum_{i \in S}\left(x_{h,i} - x_{h-1,i-1}\right).$$

In addition to the weighted average of the two estimates described above, the CPS composite estimate incorporates an adjustment which reduces variance while at the same time partially correcting for bias associated with time in sample. Results of past research have indicated that, for estimates of total unemployed, $E(x_{h,1})$ significantly exceeds $E(Y_h)$. (See Bailar 1975.) While the causes of the time-in-sample bias are unknown, Breau and Ernst (1983) found that adding a bias adjustment term to the composite estimator reduced both the variance and the time-in-sample bias of CPS estimates. The current bias adjustment term is based on the quantity

$$\beta_h = \frac{1}{8}\left\{\sum_{i \notin S} x_{h,i} - \frac{1}{3}\sum_{i \in S} x_{h,i}\right\},$$

which serves to reweight the estimates from the various rotation groups, assigning slightly more weight to data from persons completing their first or fifth interviews in month *h*. Note that if all the $x_{h,i}$'s had the same mean, β_h would have mean zero.

Incorporating both the weighted average and the bias adjustment term, the CPS composite estimator takes the form

$$Y_h'' = (1-K)Y_h + K\left(Y_{h-1}'' + \Delta_h\right) + A\beta_h,$$

where *A* and *K* are constant parameters between zero and one. The CPS composite estimator is often called an "*AK* estimator," because it involves these constant coefficients. Currently, the estimator is applied with *A* = .2 and *K* = .4 for all labor force categories. These values are approximately optimal for monthly estimates of unemployment level.

Optimal values of *A* and *K* for monthly labor force totals, however, depend both on the time-in-sample bias pattern and on the correlation structure of the labor force estimates across time. Since these vary by labor force category—estimates for employed, for example, are more strongly correlated than those for unemployed—optimal values for the compositing coefficients also vary. Moreover, in January 1994, a new questionnaire and data collection method were introduced in the CPS; these may affect the time-in-sample bias. Estimating the new bias pattern will require data from several months following January 1994.

Due to differences in the correlation structures of CPS estimates, using different *A* and *K* parameters for different labor force categories would improve accuracy. At the same time, however, varying the coefficients could render some estimates inconsistent with one another. By definition, for example, the civilian labor force comprises persons who are either employed or unemployed. Use of different compositing coefficients for these three categories could result in estimates of total employed and total unemployed that fail to sum to the estimated level of the civilian labor force. Also, as discussed above, CPS population estimates must reflect the population distributions of certain demographic traits, as estimated through the decennial census. Widely varying compositing coefficients could alter the distributions of these traits in CPS sample population estimates computed as sums of composited labor force estimates.

The "composite weighting" approach, suggested by Fuller (1990), eliminates the problem of inconsistent estimates by introducing a second raking ratio adjustment, similar to the one now used in the CPS. This time, however, the composite estimated labor force totals would take the place of population estimates, forcing the resulting person weights within each labor force category to sum to the composite estimate. The actual raking could be performed in a variety of ways, as discussed in Section 4.

3. Selecting Compositing Coefficients for Labor Force Categories. In this research we apply different pairs of *A*,*K* compositing parameters for measuring different characteristics. The choice of values for *A* and *K*, however, is still not obvious. A pair which works well for estimating monthly level may not perform as well when estimating month-to-month change or annual average.

For evaluating the proposed technique, we selected *A* = .3 and *K* = .4 when estimating the number of people unemployed, and *A* = .4 and *K* = .7 for the number employed. Each of these pairs represents a compromise across the important measurements.

It should be noted that the methods and results presented in this paper apply to *AK* estimators. As has been observed by Breau and Ernst (1983) and Gurney and Daly (1965), estimators which allow more general coefficients can effect further reductions in the variances, especially when measuring annual average. The accompanying biases, however, may be larger in these cases.

3.1. Criteria for Selecting the Coefficients. For any labor force characteristic, the estimates for different months from the same rotation group are correlated because of their common respondents. If $x_{h,i}$ and $x_{h-r,j}$ represent estimators from the same rotation group *r* months apart, the values are correlated as a function of *r*. When measuring the number of people unemployed, previous studies (Breau and Ernst 1983; Adam and Fuller 1992) yield correlations of about .50 when *r* is 1, decreasing to about .20 when *r* is 15. Corresponding values for the number of employed are considerably larger, dropping from about .80 to under .60 over fifteen months. In our study, we used correlations slightly smoothed from those obtained in the given references.

Estimates for the different characteristics also exhibit different patterns of bias across the eight months in sample. For this study, however, we selected the *A,K* pairs based on comparisons of variance rather than mean squared error. CPS month-in-sample bias patterns have probably changed since January 1994, when a new questionnaire was introduced and laptop computers replaced paper and pencil in the data collection process. It will be a while before good estimates of the new bias patterns are available.

For any labor force characteristic, we must consider three measurements when choosing the parameters *A* and *K*: monthly level, month-to-month change, and annual average. The importance of the first two is not in question. But annual average is critical for many state CPS estimates. Of the 50 states and the District of Columbia, 40 do not have samples large enough to meet reliability requirements on a monthly basis. For these smaller states, the annual average for labor force characteristics is a key measure. A cursory look at the form of the *AK* estimator in Section 2.2 shows that changing *K* gives conflicting results: while increasing *K* can help reduce the variance of month-to-month change, it generally amplifies the variance of annual average.

The choice of coefficients to use came down to computing three variances for each *A,K* pair and comparing the sets across all *A,K* pairs. As no one pair yielded the smallest variances for all three measurements, a compromise was necessary.

3.2 The Selections. Though the variance formulas required for selecting optimal parameters *A* and *K* are found in Cantwell (1990), solving for optimal *A* and *K* would be a formidable task. We therefore computed variances for all combinations of *A* and *K* equal to 0,.1,.2,...,.9. Except at the extremes (*A* and *K* near 0 or .9), the variances do not change rapidly with changing *A* and *K*.

For estimating the number of people unemployed, we selected A = .3 and K = .4. This pair is optimal, among the 100 pairs observed, for measuring monthly level; it is close to optimal when measuring month-to-month change and annual average. A similar situation arises when we estimate the number of people employed. The optimal pair for measuring monthly level, A = .4 and K = .7, fares well for all three measures. So for estimating unemployed and employed, the selections which minimize the variances of monthly levels are good compromise choices.

4. Computing CPS Composite Weights. The first step in Fuller's method of computing composite weights is to compute the composite estimates which will serve as "controls" in the raking adjustment. The raking process we apply will differ slightly according to the level of the controls. We consider two basic approaches:

1. Compute composite labor force estimates only for the nation as a whole. We will refer to the resulting composite weights as *national composite weights.*
2. Compute separate composite estimates for each of the demographic subgroups represented in the CPS raking ratio adjustment. We will call the resulting weights *marginal composite weights.*

In our empirical study of these alternatives, we consider only data from respondents aged sixteen or older.

In the first approach, we composite the national estimates for two labor force categories—employed and unemployed—using values of *A* and *K* selected specifically for each category, as described in the previous section. The civilian labor force, by definition, comprises persons falling into one of these two categories; thus the sum of the composite estimates for employed and unemployed is a reasonable estimate of the number of people in the civilian labor force. An estimate of the number of people *not* in the labor force may then be obtained by subtracting this estimate from the national population control. The raking procedure that follows is identical to the CPS raking ratio adjustment, *except* a fourth dimension of raking is added: raking to the national composite labor force estimates.

The second approach requires computing composite estimates for the three main labor force categories within each demographic group used in the raking ratio adjustment. The method used to compute the composite estimates is analogous to the one used at the national level. The three-dimensional reraking process, however, must be carried out separately for each labor force category; it proceeds just as the current raking ratio adjustment, but the composite estimates for the given category take the place of the population controls.

Since replicate weights, computed by generalized replication (see Fay 1989) were available for 1987 CPS data, we used these weights to compute composite replicate weights by the two methods mentioned above. From the composite replicate weights we estimated the variances of labor force estimates computed from each set of composite weights.

4.1. Raking to National Composite Estimates. We performed the four-dimensional raking adjustment using national composite estimates on CPS data from April through December, 1987. Typical adjustment factors used in this method fell very close to 1.0: compositing appeared to have little effect on the national labor force estimates. This seemed reasonable because, as explained above, the composite estimator is based on a weighted average of two estimators. When the sample is large, as in the case of the national estimates, the variances of both estimators are relatively low, so the difference between estimates obtained from them is usually slight. The difference between national CPS ratio estimates and composite estimates is correspondingly small, resulting in adjustment factors close to 1.0.

Since the bias patterns of CPS estimates have probably changed due to the new data collection method, we used the coefficients of variation (CV's) to evaluate the accuracy of labor force estimates computed from the national composite weights. The CV's of subnational estimates computed from the national composite weights consistently exceeded those of the optimal composite estimates. For employment levels and estimated numbers of people not in the labor force, differences in the CV's for the two sets of estimates were especially marked. We used the estimated CV's for the eleven largest states to test the significance of the loss of reliability that would result from using the national composite weights. Because of the positive correlation of the estimates across months, we averaged the nine monthly estimates of CV for each state and each estimation method (optimal composite and national composite weights). We then computed a ratio of CV's for each state, dividing the average CV for the national composite weight estimates by that for the optimal composite estimates. T-tests performed on the state CV ratios for each labor force category gave the results shown in Table 1. The null hypothesis—that the ratios have a mean of one—is equivalent to the assumption of no significant difference in the reliability of optimal composite estimates and estimates computed from the national composite weights. As indicated by the p-values, all the t-statistics are significant at the 0.05 level, implying that the reliability lost by use of the national composite weights is significant.

Table 1. Results of T-test for State CV Ratios

	EMP	UE	NILF
Mean CV Ratio	1.1155	1.0165	1.1146
t-statistic	9.0212	2.9715	8.6360
p-value	0.0001	0.0140	0.0001

4.2. Raking to Composite Estimates by Demographic Group. Because of the reliability problems with the national composite weights, we also computed marginal composite weights for 1987 data. As mentioned, producing marginal composite weights requires a separate raking process for each of the three main labor force categories (employed, unemployed, and not in the labor force). For estimates of employment level, none of the demographic groups used in the CPS raking adjustment proved too small to support reasonable composite estimates. Six iterations of raking were sufficient to virtually reproduce the optimal composite estimates for all states and demographic groups as sums of marginal composite weights. The marginal composite weights thus outperformed the national composite weights for monthly subnational estimates of employment level.

Producing marginal composite weights for the unemployed category, however, proved more problematic. Unemployed sample persons for some of the age/sex/race groups used in the raking adjustment —notably those including mainly persons of retirement age—often numbered in the single digits; in some data months, we had no unemployed sample for some of these older groups. In these cases, the composite estimates of unemployment level occasionally strayed below zero. We also observed small sample counts for some Hispanic age/sex groups used in the ratio adjustment, indicating the possibility of negative composite estimates, though none actually occurred in the data we analyzed.

Table 2. Cells Collapsed in Computation of Marginal Composite Weights: *Unemployed*

	Age Cells	Average Sample Count	Collapsed Cells
White Male	60-62	33.9	White Male 60+
	63-64	12.0	
	65-67	9.0	
	68-69	4.8	
	70-74	6.2	
	75+	2.8	
White Female	60-62	21.2	White Female 60+
	63-64	8.4	
	65-67	7.0	
	68-69	3.0	
	70-74	4.0	
	75+	2.6	
Black Male	45-49	18.4	Black Male 45+
	50-54	12.6	
	55-59	9.0	
	60-64	7.7	
	65+	2.6	
Black Female	45-49	21.3	Black Female 45+
	50-54	11.3	
	55-59	8.1	
	60-64	4.4	
	65+	2.1	
Other Male	16-44	90.4	Other Male 16+
	45+	18.1	
Other Female	16-44	68.1	Other Fem. 16+
	45+	9.7	
Hispanic Male	30-49	66.4	Hispanic Male 30+
	50+	21.2	
Hispanic Female	30-49	50.7	Hispanic Fem. 30+
	50+	11.4	

Demographic cells with unusually high or low sample population estimates—usually due to low sample counts—are routinely collapsed with other cells in the CPS raking ratio adjustment. The collapsing algorithm, however, results in different collapsing patterns for different months (and even for different rotation groups in the same month). Since computing marginal composite weights requires compositing estimates *across* months, varying cell definitions from month to month would complicate implementation considerably. We chose instead to seek one set of permanent cell definitions which would (1) ensure sufficient sample in each cell to provide reasonable composite estimates and (2) result in minimal loss of reliability in the labor force estimates computed from the marginal composite weights.

Our collapsing of cells was based on sample counts: to provide reasonable composite estimates, we wanted at least ten sample persons per cell. Since sample counts vary from month to month, it seemed desirable to collapse cells whose sample counts rarely exceeded a dozen, even if the counts for these cells never fell below ten for the 1987 data months we analyzed. Given the loss of reliability that resulted from using national composite weights, however, we were also concerned that too much collapsing might increase the CV's of labor force estimates computed from the marginal composite weights.

We computed marginal composite weights for 1987 unemployment data (April through December) using several alternative collapsing plans, which involved different lower bounds for the average sample count or for the minimum sample count obtained from our nine data months. Estimated CV's of the resulting unemployment totals indicated that collapsing the smaller cells had little effect on the reliability of estimates computed from the composite weights. Table 2 shows the average sample counts for the smaller age/sex/ethnicity cells and age/sex/race cells and indicates the collapsing pattern we found most desirable. Since it involved collapsing all cells whose minimum sample counts fell below twelve, we were confident that it would ensure sufficient sample to provide reasonable composite estimates for all cells.

For certain cells, collapsing was clearly necessary: unemployment estimates for the older age groups considered in the age/sex/race adjustment consistently suffered from low sample counts. In cases where the need for collapsing was disputable, however, we performed statistical tests to determine whether or not the collapsing would significantly increase the CV's of estimates computed from the composite weights. For demographic groups affected by such collapsing, we considered the ratio of the CV of the unemployment estimate computed from the marginal composite weights to the CV of the corresponding optimal composite estimate. Let

$$r = \frac{CV(\hat{X}_m)}{CV(\hat{X}_o)},$$

where

$\hat{X}_m$ = an unemployment estimate computed from marginal composite weights;

and

$\hat{X}_o$ = the corresponding optimal composite estimate of unemployment.

For each data month *i*, *i* = 1,...,9, we computed $\hat{r}_i$, an estimate of *r*, for each of several demographic groups. We used these nine observations to test the hypothesis that the effect of the cell collapsing shown in Table 2 did not significantly affect the reliability of important unemployment estimates computed from the marginal composite weights. That is, we tested

$$H_0: \; r = 1,$$

for each demographic group.

The results of the t-tests for the collapsing of age cells in the "other races" category are shown in Table 3. Due to positive correlation between the estimated CV ratios for different months, the t-statistics are conservative in the sense that they support rejection more often than the usual nominal level (under no correlation) would indicate. Since none of the test statistics are significant, the effect of the cell collapsing on the CV's of the estimates is negligible. Thus the collapsing of age cells within each sex group in the "other races" category appears appropriate: all the p-values in Table 3 are too high to allow rejection of H_0.

Table 3. Tests for Loss of Reliability Due to Collapsing Age/Sex/Race Cells: *Unemployed*

	Mean $\hat{r}_i$	t-stat.	p-value
Other Male 16-44	1.0088	1.0091	0.3425
Other Male 45+	1.0315	0.8916	0.3986
Other Fem. 16-44	1.0098	0.8726	0.4083
Other Fem. 45+	0.9474	-1.2009	0.2641

5. Summary. We can improve reliability of CPS labor force estimates by using different *AK* compositing coefficients for different labor force categories. To ensure that estimated labor force totals equal the sums of their estimated components, Fuller (1990) suggested incorporating the effect of composite estimation into CPS micro data weights through a procedure similar to the raking ratio adjustment now used in the CPS. Composite estimates may then be computed as sums of these composite weights.

In our research on computing CPS composite weights, we consider two possible methods, each based on a ratio adjustment applied to the micro data weights to force the weights in a given labor force category to sum to a composite estimate. The methods differ in that the composite estimates used as "controls" in the ratio adjustment are computed at a different level for each method. The first method—computing composite estimates at the national level—appears to result in subnational estimates whose reliability falls significantly below that of the optimal *AK* composite estimates. In the second method, we compute composite estimates for each demographic group represented in the current CPS raking ratio adjustment and then perform a separate raking adjustment for each labor force category. Though some collapsing of demographic groups is needed to allow implementation for the unemployed category, this method provides labor force estimates for states and important demographic subgroups that virtually equal the corresponding optimal *AK* composite estimates.

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